Science texts (endocrine) final stats imac

Code

Experiment 2: Endocrine Text

Hide

```
library(afex)
```

```
Loading required package: lme4
Loading required package: Matrix
************
Welcome to afex. For support visit: http://afex.singmann.science/
- Functions for ANOVAs: aov_car(), aov_ez(), and aov_4()
- Methods for calculating p-values with mixed(): 'S', 'KR', 'LRT', and 'PB'
- 'afex_aov' and 'mixed' objects can be passed to emmeans() for follow-up tests
- NEWS: emmeans() for ANOVA models now uses model = 'multivariate' as default.
- Get and set global package options with: afex_options()
- Set orthogonal sum-to-zero contrasts globally: set_sum_contrasts()
- For example analyses see: browseVignettes("afex")
************

Attaching package: ‘afex’

The following object is masked from ‘package:lme4’:

    lmer
```

Hide

```
library(emmeans)
library(ltm)
```

```
Loading required package: MASS
Loading required package: msm
Loading required package: polycor
```

Hide

```
library(tidyverse)
```

```
Registered S3 methods overwritten by 'dbplyr':
  method         from
  print.tbl_lazy
  print.tbl_sql
── Attaching packages ─────────────────────────────────────────────────── tidyverse 1.3.2 ──✔ ggp
lot2 3.4.0      ✔ purrr   0.3.5
✔ tibble  3.1.8      ✔ dplyr   1.0.10
✔ tidyr   1.2.1      ✔ stringr 1.4.1
✔ readr   2.1.3      ✔ forcats 0.5.2 ── Conflicts ───────────────────────────────────────────────
─────── tidyverse_conflicts() ──
✖ tidyr::expand() masks Matrix::expand()
✖ dplyr::filter() masks stats::filter()
✖ dplyr::lag()    masks stats::lag()
✖ tidyr::pack()   masks Matrix::pack()
✖ dplyr::select() masks MASS::select()
✖ tidyr::unpack() masks Matrix::unpack()
```

Hide

```
library(interactions)
library(cowplot)

# home_dir = "/Volumes/GoogleDrive/My Drive/grad_school/DML_WBR/dissertation_drive/cna_recall/rifa
_exp2_mturk/"
# home_dir = "/Volumes/GoogleDrive/My Drive/grad_school/DML_WBR/dissertation_drive/cna_recall/rifa
_exp2_endo/"
home_dir = getwd()
# df = read.csv(paste(home_dir,"MC_for_stats_in_r_n=170_11_8_21.csv",sep=""),header=TRUE) # viruse
s
df = read.csv(paste(home_dir,"MC_for_stats_in_r_n=190_8_7_22.csv",sep="/"),header=TRUE) # endocrin
e
# str(df)
df$q_num = as.factor(df$q_num)
df$subjectGroup = recode(df$subjectGroup, "nsg:1"="RPm","nsg:2"="RPp", "nsg:3"= "NRP")
df$subjectGroup = factor(df$subjectGroup,levels=c("RPm","RPp","NRP"))

add = read.csv(paste(home_dir,"endocrine_GMRT_familiarity_transformed.csv",sep="/"))
df = left_join(add,df,by="mturk_id")

df = df[,c("mturk_id","subjectGroup","GMRT_bc_c_s","familiarity_bc_c_s","q_num","q_type","correc
t")]
df = df %>% rename("Reading_Ability"= GMRT_bc_c_s,"Prior_Knowledge" = familiarity_bc_c_s)

start.time <- Sys.time()
```

Multiple Choice

Model Selection

Hide

```
# mm1.g = glmer(data=df,formula=(correct ~ subjectGroup * q_type * Reading_Ability * Prior_Knowled
ge  + (q_type|mturk_id) + (1|q_num)),family=binomial(link='logit'),control = glmerControl(optCtrl
= list(maxfun = 1e6)))

# gm_all <- lme4::allFit(mm1.g) # almost all except Nelder_Mead (failed to converge) are singular

# mm2.g = glmer(data=df,formula=(correct ~ subjectGroup * q_type * Reading_Ability * Prior_Knowled
ge  + (q_type||mturk_id) + (1|q_num)),family=binomial(link='logit'), control = glmerControl(optCtr
l = list(maxfun = 1e6)))

# gm_all2 <- lme4::allFit(mm2.g) # almost all except Nelder_Mead (failed to converge) are singular

# summary(mm2.g)$varcor
# # random slope estimate for q_type is very small

mm3.g = glmer(data=df,formula=(correct ~ subjectGroup * q_type * Reading_Ability * Prior_Knowledge
+ (1|mturk_id) + (1|q_num)),family=binomial(link='logit'), control = glmerControl(optCtrl = list(m
axfun = 1e6),optimizer="bobyqa"))

# gm_all3 <- lme4::allFit(mm3.g) # 4 failed to converge

# check estimates of different optimizers, if they are practically equivalent, convergence warning
is probably false positive
# Therefore use whichever converges fastest

# ss = summary(gm_all3)
# ss$ fixef                ## fixed effects
#   ss$ llik                 ## log-likelihoods
#   ss$ sdcor                ## SDs and correlations
#   ss$ theta                ## Cholesky factors
#   ss$ which.OK             ## which fits worked

# Resulsts are practically identical, therefore will proceed to use bobyqa and mm3.g as final mode
l
```

Multiple Choice Final Model

Hide

```
# no random slope for q_type
require(parallel)
```

```
Loading required package: parallel
```

Hide

```
cl <- makeCluster(rep("localhost", 6)) # make cluster
#
mm3 = afex::mixed(cl=cl,data=df,formula=(correct ~ subjectGroup * q_type * Reading_Ability * Prior
_Knowledge  + (1|mturk_id) + (1|q_num)), family=binomial(link='logit'),method="PB",args_test = lis
t(nsim = 1000, cl = cl),progress=TRUE,expand_re = TRUE,control = glmerControl(optCtrl = list(maxfu
n = 1e6),optimizer="bobyqa"))
```

```
Contrasts set to contr.sum for the following variables: subjectGroup, q_type, mturk_id, q_num
```

```
Fitting 16 (g)lmer() models.
Obtaining 15 p-values:
[...............]
```

Hide

```
stopCluster(cl)
```

Hide

```
contrasts(mm3$data$subjectGroup)
```

```
    [,1] [,2]
RPm    1    0
RPp    0    1
NRP   -1   -1
```

Hide

```
mm3
```

```
Mixed Model Anova Table (Type 3 tests, PB-method)

Model: correct ~ subjectGroup * q_type * Reading_Ability * Prior_Knowledge +
Model:     (1 | mturk_id) + (1 | q_num)
Data: df
                                              Effect df    Chisq p.value
1                                       subjectGroup  2     4.73    .122
2                                             q_type  1     0.01    .919
3                                    Reading_Ability  1 51.80 **    .001
4                                    Prior_Knowledge  1   4.02 +    .053
5                                subjectGroup:q_type  2   6.63 +    .051
6                       subjectGroup:Reading_Ability  2     0.15    .938
7                             q_type:Reading_Ability  1     0.21    .671
8                       subjectGroup:Prior_Knowledge  2     0.13    .938
9                             q_type:Prior_Knowledge  1     0.03    .836
10                   Reading_Ability:Prior_Knowledge  1     0.00    .992
11               subjectGroup:q_type:Reading_Ability  2     2.00    .417
12               subjectGroup:q_type:Prior_Knowledge  2     1.72    .441
13      subjectGroup:Reading_Ability:Prior_Knowledge  2     1.66    .470
14            q_type:Reading_Ability:Prior_Knowledge  1     1.01    .321
15 subjectGroup:q_type:Reading_Ability:Prior_Knowledge  2     1.76    .437
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘+’ 0.1 ‘ ’ 1
```

Hide

```
summary(mm3$full_model)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [glmerMod]
 Family: binomial  ( logit )
Formula: correct ~ subjectGroup * q_type * Reading_Ability * Prior_Knowledge +
    (1 | mturk_id) + (1 | q_num)
   Data: data
Control: glmerControl(optCtrl = list(maxfun = 1e+06), optimizer = "bobyqa")

     AIC      BIC   logLik deviance df.resid
  2178.3   2327.3  -1063.1   2126.3     2254

Scaled residuals:
    Min      1Q  Median      3Q     Max
-6.5097 -0.4151  0.3197  0.4897  3.0561

Random effects:
 Groups   Name        Variance Std.Dev.
 mturk_id (Intercept) 0.4601   0.6783
 q_num    (Intercept) 1.1587   1.0764
Number of obs: 2280, groups:  mturk_id, 190; q_num, 12

Fixed effects:
                                                         Estimate Std. Error z value
(Intercept)                                             1.3977727  0.3221340   4.339
subjectGroup1                                          -0.0109825  0.1146441  -0.096
subjectGroup2                                          -0.2043121  0.1100588  -1.856
q_type1                                                 0.0371643  0.3169429   0.117
Reading_Ability                                         0.6194469  0.0826092   7.499
Prior_Knowledge                                         0.1654945  0.0815433   2.030
subjectGroup1:q_type1                                   0.0289357  0.0850882   0.340
subjectGroup2:q_type1                                   0.1722129  0.0821217   2.097
subjectGroup1:Reading_Ability                           0.0373917  0.1200749   0.311
subjectGroup2:Reading_Ability                          -0.0384482  0.1081635  -0.355
q_type1:Reading_Ability                                 0.0284464  0.0617233   0.461
subjectGroup1:Prior_Knowledge                           0.0398135  0.1197482   0.332
subjectGroup2:Prior_Knowledge                          -0.0347471  0.1125424  -0.309
q_type1:Prior_Knowledge                                -0.0105932  0.0614661  -0.172
Reading_Ability:Prior_Knowledge                         0.0005715  0.0777560   0.007
subjectGroup1:q_type1:Reading_Ability                   0.0617260  0.0897623   0.688
subjectGroup2:q_type1:Reading_Ability                   0.0623524  0.0805564   0.774
subjectGroup1:q_type1:Prior_Knowledge                  -0.0179487  0.0895600  -0.200
subjectGroup2:q_type1:Prior_Knowledge                  -0.0871594  0.0849587  -1.026
subjectGroup1:Reading_Ability:Prior_Knowledge           0.1525226  0.1186422   1.286
subjectGroup2:Reading_Ability:Prior_Knowledge          -0.0524850  0.1025775  -0.512
q_type1:Reading_Ability:Prior_Knowledge                -0.0600049  0.0587797  -1.021
subjectGroup1:q_type1:Reading_Ability:Prior_Knowledge   0.0937051  0.0895206   1.047
subjectGroup2:q_type1:Reading_Ability:Prior_Knowledge  -0.0986707  0.0776864  -1.270
                                                       Pr(>|z|)
(Intercept)                                            1.43e-05 ***
subjectGroup1                                            0.9237
subjectGroup2                                            0.0634 .
q_type1                                                  0.9067
Reading_Ability                                        6.45e-14 ***
Prior_Knowledge                                          0.0424 *
subjectGroup1:q_type1                                    0.7338
```

```
subjectGroup2:q_type1                                  0.0360 *
subjectGroup1:Reading_Ability                          0.7555
subjectGroup2:Reading_Ability                          0.7222
q_type1:Reading_Ability                                0.6449
subjectGroup1:Prior_Knowledge                          0.7395
subjectGroup2:Prior_Knowledge                          0.7575
q_type1:Prior_Knowledge                                0.8632
Reading_Ability:Prior_Knowledge                        0.9941
subjectGroup1:q_type1:Reading_Ability                  0.4917
subjectGroup2:q_type1:Reading_Ability                  0.4389
subjectGroup1:q_type1:Prior_Knowledge                  0.8412
subjectGroup2:q_type1:Prior_Knowledge                  0.3049
subjectGroup1:Reading_Ability:Prior_Knowledge          0.1986
subjectGroup2:Reading_Ability:Prior_Knowledge          0.6089
q_type1:Reading_Ability:Prior_Knowledge                0.3073
subjectGroup1:q_type1:Reading_Ability:Prior_Knowledge   0.2952
subjectGroup2:q_type1:Reading_Ability:Prior_Knowledge   0.2040
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

```
Correlation matrix not shown by default, as p = 24 > 12.
Use print(x, correlation=TRUE)  or
    vcov(x)        if you need it
```

Hide

```
# arm::binnedplot(fitted(mm3$full_model),
#             residuals(mm3$full_model, type = "response"),
#             nclass = NULL,
#             cex.pts = 0.8,
#             col.pts = 1,
#             col.int = "gray")
```

subjectGroup by question type interaction

Hide

```
emm_options(glmer.df = "asymptotic")
emm_1 <- emmeans(mm3, "subjectGroup",by="q_type")
```

```
NOTE: Results may be misleading due to involvement in interactions
```

Hide

```
pairs(emm_1,adjust=NULL)
```

```
q_type = inference:
 contrast  estimate    SE  df z.ratio p.value
 RPm - RPp  0.05005 0.248 Inf   0.202  0.8400
 RPm - NRP  0.00381 0.246 Inf   0.015  0.9877
 RPp - NRP -0.04625 0.239 Inf  -0.193  0.8467

q_type = memory:
 contrast  estimate    SE  df z.ratio p.value
 RPm - RPp  0.33661 0.236 Inf   1.426  0.1539
 RPm - NRP -0.45636 0.250 Inf  -1.824  0.0681
 RPp - NRP -0.79297 0.239 Inf  -3.323  0.0009

Results are given on the log odds ratio (not the response) scale.
```

Hide

```
# summary(mm3$full_model)
```

Recall

Hide

```
# home_dir = "/Volumes/GoogleDrive/My Drive/grad_school/DML_WBR/dissertation_drive/cna_recall/rifa
_exp2_endo/"
home_dir = getwd()
df = read.csv(paste(home_dir,"binary_correct_n=190_10_21_22.csv",sep="/"),header=TRUE)
df$subjectGroup = recode(df$subjectGroup,"nsg:3"= "NRP", "nsg:1"="RPm","nsg:2"="RPp" )
df$subjectGroup = factor(df$subjectGroup, c("RPm","RPp","NRP"))

df$idea_units = as.factor(df$idea_units)

add = read.csv(paste(home_dir,"endocrine_GMRT_familiarity_transformed.csv",sep="/"))
df = left_join(add,df,by="mturk_id")

df = df[,c("mturk_id","subjectGroup","GMRT_bc_c_s","familiarity_bc_c_s","idea_units","correct","RP
_any","RP_imp","RP_per")]
df = df %>% rename("Reading_Ability"= GMRT_bc_c_s,"Prior_Knowledge" = familiarity_bc_c_s)
```

Main Idea Units

Hide

```
dfRPi = df[df$RP_imp == 1,]
```

Hide

```
mm.RPi1.g = glmer(data=dfRPi,correct ~ subjectGroup * Reading_Ability * Prior_Knowledge  + (1|mtur
k_id) + (1|idea_units),family=binomial(link='logit'),control = glmerControl(optCtrl = list(maxfun
= 1e6),optimizer = "bobyqa"))

# gm_all <- lme4::allFit(mm.RPi1.g) #

# ss <- summary(gm_all)
# ss$ fixef               ## fixed effects
# ss$ llik                ## log-likelihoods
# ss$ sdcor               ## SDs and correlations
# ss$ theta               ## Cholesky factors
# ss$ which.OK            ## which fits worked
# nearly identical, so will use boyqa for speed
```

Hide

```
require(parallel)
cl <- makeCluster(rep("localhost", 6)) # make cluster
mm.RPi1 = afex::mixed(cl=cl,data=dfRPi,formula=(correct ~ subjectGroup * Reading_Ability * Prior_K
nowledge  + (1|mturk_id) + (1|idea_units)),family=binomial(link='logit'),method="PB",args_test = l
ist(nsim = 1000, cl = cl),progress=TRUE,expand_re = TRUE,control = glmerControl(optCtrl = list(max
fun = 1e6),optimizer="bobyqa"))
```

```
Contrasts set to contr.sum for the following variables: subjectGroup, mturk_id, idea_units
```

```
Fitting 8 (g)lmer() models.
Obtaining 7 p-values:
[.......]
```

Hide

```
stopCluster(cl)
```

Hide

```
mm.RPi1
```

```
Mixed Model Anova Table (Type 3 tests, PB-method)

Model: correct ~ subjectGroup * Reading_Ability * Prior_Knowledge +
Model:     (1 | mturk_id) + (1 | idea_units)
Data: dfRPi
                                      Effect df    Chisq p.value
1                               subjectGroup  2 51.36 **    .001
2                            Reading_Ability  1  8.41 **    .006
3                            Prior_Knowledge  1   5.43 *    .026
4               subjectGroup:Reading_Ability  2     2.89    .255
5               subjectGroup:Prior_Knowledge  2     0.40    .838
6            Reading_Ability:Prior_Knowledge  1     0.01    .908
7 subjectGroup:Reading_Ability:Prior_Knowledge  2     2.68    .303
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘+’ 0.1 ‘ ’ 1
```

Hide

```
# summary(mm.RPi1$full_model,correlation=FALSE)
```

Hide

```
emm_options(glmer.df = "asymptotic")
emm_1 <- emmeans(mm.RPi1, "subjectGroup")
```

```
NOTE: Results may be misleading due to involvement in interactions
```

Hide

```
pairs(emm_1,adjust=NULL)
```

```
 contrast  estimate    SE  df z.ratio p.value
 RPm - RPp    1.696 0.285 Inf   5.940  <.0001
 RPm - NRP    1.852 0.291 Inf   6.365  <.0001
 RPp - NRP    0.156 0.294 Inf   0.531  0.5953

Results are given on the log odds ratio (not the response) scale.
```

Peripheral Idea Units

Hide

```
dfRPp = df[df$RP_per == 1,]
```

Hide

```
mm.RPp1.g = glmer(data=dfRPp,correct ~ subjectGroup * Reading_Ability * Prior_Knowledge  + (1|mtur
k_id) + (1|idea_units),family=binomial(link='logit'),control = glmerControl(optCtrl = list(maxfun
= 1e6),optimizer = "bobyqa"))

# gm_all <- lme4::allFit(mm.RPp1.g) # 4 failed to converge, compare results

# ss <- summary(gm_all)
# ss$ fixef              ## fixed effects
# ss$ llik               ## log-likelihoods
# ss$ sdcor              ## SDs and correlations
# ss$ theta              ## Cholesky factors
# ss$ which.OK           ## which fits worked
# nearly identical, so will use bobyqa for speed
```

Hide

```
require(parallel)
cl <- makeCluster(rep("localhost", 6)) # make cluster
mm.RPp1 = afex::mixed(cl=cl,data=dfRPp,formula=(correct ~ subjectGroup * Reading_Ability * Prior_K
nowledge  + (1|mturk_id) + (1|idea_units)),family=binomial(link='logit'),method="PB",args_test = l
ist(nsim = 1000, cl = cl),progress=TRUE,expand_re = TRUE,control = glmerControl(optCtrl = list(max
fun = 1e6),optimizer="bobyqa"))
```

```
Contrasts set to contr.sum for the following variables: subjectGroup, mturk_id, idea_units
```

```
Fitting 8 (g)lmer() models.
Obtaining 7 p-values:
[.......]
```

Hide

```
stopCluster(cl)
```

Hide

```
mm.RPp1
```

```
Mixed Model Anova Table (Type 3 tests, PB-method)

Model: correct ~ subjectGroup * Reading_Ability * Prior_Knowledge +
Model:     (1 | mturk_id) + (1 | idea_units)
Data: dfRPp
                                    Effect df    Chisq p.value
1                             subjectGroup  2 68.90 **    .001
2                          Reading_Ability  1     0.14    .729
3                          Prior_Knowledge  1   4.53 +    .051
4             subjectGroup:Reading_Ability  2     2.02    .374
5             subjectGroup:Prior_Knowledge  2     4.23    .146
6          Reading_Ability:Prior_Knowledge  1     0.11    .748
7 subjectGroup:Reading_Ability:Prior_Knowledge  2   8.91 *    .022
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘+’ 0.1 ‘ ’ 1
```

Hide

```
# summary(mm.RPp1$full_model,correlation=FALSE)
```

Hide

```
emm_options(glmer.df = "asymptotic")
emm_1 <- emmeans(mm.RPp1, "subjectGroup")
```

```
NOTE: Results may be misleading due to involvement in interactions
```

Hide

```
pairs(emm_1,adjust=NULL)
```

```
 contrast  estimate    SE  df z.ratio p.value
 RPm - RPp   -2.715 0.460 Inf  -5.904  <.0001
 RPm - NRP    0.382 0.576 Inf   0.664  0.5065
 RPp - NRP    3.098 0.502 Inf   6.175  <.0001

Results are given on the log odds ratio (not the response) scale.
```

Hide

```
# probe_interaction(mm.RPp1$full_model, pred = Prior_Knowledge, modx = subjectGroup,mod2 = Reading
_Ability , plot.points = FALSE)
```

Hide

```
# interact_plot(mm.RPp1$full_model, pred = Prior_Knowledge, modx = subjectGroup,mod2 = Reading_Abi
lity , plot.points = TRUE,jitter = .05,point.size = .75)
```

Non-practiced Idea Units

Hide

```
dfNoRP = df[df$RP_any == 0,]
mm.noRP1.g = glmer(data=dfNoRP,correct ~ subjectGroup * Reading_Ability * Prior_Knowledge + (1|mtu
rk_id) + (1|idea_units),family=binomial(link='logit'),control = glmerControl(optCtrl = list(maxfun
= 1e6),optimizer = "bobyqa"))

# gm_all <- lme4::allFit(mm.noRP1.g) # 2 failed to converge, compare results
#
# ss <- summary(gm_all)
#   ss$ fixef               ## fixed effects
#   ss$ llik                ## log-likelihoods
#   ss$ sdcor               ## SDs and correlations
#   ss$ theta               ## Cholesky factors
#   ss$ which.OK            ## which fits worked
# nearly identical, so will use boyqa for speed
```

Hide

```
# no random slope for q_type
require(parallel)
cl <- makeCluster(rep("localhost", 6)) # make cluster
#
mm.noRP1 = afex::mixed(cl=cl,data=dfNoRP,formula=(correct ~ subjectGroup * Reading_Ability * Prior
_Knowledge + (1|mturk_id) + (1|idea_units)), family=binomial(link='logit'),method="PB",args_test =
list(nsim = 1000, cl = cl),progress=TRUE,expand_re = TRUE,control = glmerControl(optCtrl = list(ma
xfun = 1e6),optimizer="bobyqa"))
```

```
Contrasts set to contr.sum for the following variables: subjectGroup, mturk_id, idea_units
```

```
Fitting 8 (g)lmer() models.
Obtaining 7 p-values:
[.......]
```

Hide

```
stopCluster(cl)
```

Hide

```
mm.noRP1
```

```
Mixed Model Anova Table (Type 3 tests, PB-method)

Model: correct ~ subjectGroup * Reading_Ability * Prior_Knowledge +
Model:     (1 | mturk_id) + (1 | idea_units)
Data: dfNoRP
                                        Effect df    Chisq p.value
1                                 subjectGroup  2     0.67    .726
2                              Reading_Ability  1  8.70 **    .008
3                              Prior_Knowledge  1 18.83 **    .001
4                 subjectGroup:Reading_Ability  2     2.49    .335
5                 subjectGroup:Prior_Knowledge  2     0.31    .875
6              Reading_Ability:Prior_Knowledge  1     0.00    .975
7 subjectGroup:Reading_Ability:Prior_Knowledge  2   8.66 *    .012
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘+’ 0.1 ‘ ’ 1
```

Hide

```
summary(mm.noRP1)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace Approximation) [glmerMod]
 Family: binomial  ( logit )
Formula: correct ~ subjectGroup * Reading_Ability * Prior_Knowledge +
    (1 | mturk_id) + (1 | idea_units)
   Data: data
Control: glmerControl(optCtrl = list(maxfun = 1e+06), optimizer = "bobyqa")

     AIC      BIC   logLik deviance df.resid
  4725.1   4817.2  -2348.6   4697.1     5306

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.5256 -0.4844 -0.3100 -0.1583  7.4323

Random effects:
 Groups     Name        Variance Std.Dev.
 mturk_id   (Intercept) 0.6383   0.7989
 idea_units (Intercept) 0.8609   0.9279
Number of obs: 5320, groups:  mturk_id, 190; idea_units, 28

Fixed effects:
                                               Estimate Std. Error z value Pr(>|z|)
(Intercept)                                   -1.744164   0.191831  -9.092  < 2e-16 ***
subjectGroup1                                 -0.060582   0.108275  -0.560  0.57581
subjectGroup2                                 -0.022518   0.103177  -0.218  0.82724
Reading_Ability                                0.224135   0.075070   2.986  0.00283 **
Prior_Knowledge                                0.332960   0.075118   4.432 9.32e-06 ***
subjectGroup1:Reading_Ability                  0.118598   0.111208   1.066  0.28622
subjectGroup2:Reading_Ability                 -0.157738   0.101099  -1.560  0.11871
subjectGroup1:Prior_Knowledge                 -0.054336   0.111222  -0.489  0.62517
subjectGroup2:Prior_Knowledge                  0.051360   0.103963   0.494  0.62129
Reading_Ability:Prior_Knowledge               -0.002733   0.070603  -0.039  0.96913
subjectGroup1:Reading_Ability:Prior_Knowledge  0.185364   0.107095   1.731  0.08348 .
subjectGroup2:Reading_Ability:Prior_Knowledge  0.109395   0.093348   1.172  0.24123
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) sbjcG1 sbjcG2 Rdng_A Prr_Kn sbG1:R_A sbG2:R_A sG1:P_ sG2:P_ R_A:P_
subjectGrp1  0.038
subjectGrp2 -0.014 -0.530
Redng_Ablty -0.028 -0.258  0.112
Prir_Knwldg -0.003  0.140 -0.055 -0.221
sbjctG1:R_A -0.100 -0.230  0.135  0.134 -0.106
sbjctG2:R_A  0.046  0.142  0.020 -0.136  0.083 -0.508
sbjctG1:P_K  0.052  0.104 -0.068 -0.107  0.136 -0.276    0.136
sbjctG2:P_K -0.022 -0.069 -0.028  0.082 -0.054  0.132   -0.180   -0.546
Rdng_Ab:P_K -0.083 -0.108  0.087 -0.040 -0.090  0.153   -0.040   -0.272  0.188
sG1:R_A:P_K -0.042 -0.266  0.120  0.150 -0.265  0.065   -0.065   -0.259  0.110  0.198
sG2:R_A:P_K  0.034  0.131 -0.169 -0.040  0.198 -0.068   -0.076    0.118  0.045 -0.191
            sG1:R_A:
subjectGrp1
subjectGrp2
Redng_Ablty
```

```
Prir_Knwldg
sbjctG1:R_A
sbjctG2:R_A
sbjctG1:P_K
sbjctG2:P_K
Rdng_Ab:P_K
sG1:R_A:P_K
sG2:R_A:P_K -0.522
```

Hide

```
# emm_options(glmer.df = "asymptotic") # also possible: 'satterthwaite', 'kenward-roger'
# emm_1 <- emmeans(mm.noRP1, "subjectGroup")
# pairs(emm_1,adjust=NULL)
```

Hide

```
# summary(mm.noRP1$full_model,correlation=FALSE)
```

Hide

```
probe_interaction(mm.noRP1$full_model, pred = Prior_Knowledge, modx = subjectGroup,mod2 = Reading_
Ability , plot.points = FALSE)
```

```
Warning: Johnson-Neyman intervals are not available for factor moderators.
```

```
██████████████ While Reading_Ability (2nd moderator) = -9.974587e-01 (- 1 SD) ██████████████

SIMPLE SLOPES ANALYSIS

Slope of Prior_Knowledge when subjectGroup = RPm:

  Est.   S.E.   z val.      p
------ ------ -------- ------
  0.10   0.24     0.41   0.68

Slope of Prior_Knowledge when subjectGroup = RPp:

  Est.   S.E.   z val.      p
------ ------ -------- ------
  0.28   0.15     1.90   0.06

Slope of Prior_Knowledge when subjectGroup = NRP:

  Est.   S.E.   z val.      p
------ ------ -------- ------
  0.63   0.17     3.83   0.00

███████████████ While Reading_Ability (2nd moderator) =  2.652953e-17 (Mean) ███████████████

SIMPLE SLOPES ANALYSIS

Slope of Prior_Knowledge when subjectGroup = RPm:

  Est.   S.E.   z val.      p
------ ------ -------- ------
  0.28   0.14     1.96   0.05

Slope of Prior_Knowledge when subjectGroup = RPp:

  Est.   S.E.   z val.      p
------ ------ -------- ------
  0.38   0.12     3.08   0.00

Slope of Prior_Knowledge when subjectGroup = NRP:

  Est.   S.E.   z val.      p
------ ------ -------- ------
  0.34   0.12     2.77   0.01

██████████████ While Reading_Ability (2nd moderator) =  9.974587e-01 (+ 1 SD) ██████████████

SIMPLE SLOPES ANALYSIS

Slope of Prior_Knowledge when subjectGroup = RPm:

  Est.   S.E.   z val.      p
------ ------ -------- ------
  0.46   0.16     2.97   0.00
```

```
Slope of Prior_Knowledge when subjectGroup = RPp:

  Est.   S.E.   z val.      p
------ ------ --------- ------
  0.49   0.18     2.74   0.01

Slope of Prior_Knowledge when subjectGroup = NRP:

  Est.   S.E.   z val.      p
------ ------ --------- ------
  0.04   0.17     0.22   0.82
```

Hide

```
# interact_plot(mm.noRP1.g, pred = Prior_Knowledge, modx = subjectGroup,mod2 = Reading_Ability , p
lot.points = FALSE)
```

Hide

```
end.time <- Sys.time()
round((end.time - start.time), 3)
```

```
Time difference of 1.407 days
```